From State Estimation for Dogs to the Internet of Dogs

Wang Youwen, Huang Qian, Chen Sisi and Zhu Chaozheng

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Youwen Wang, Qian Huang
College of Computer and Information
Hohai University
Nanjing, China
E-mail: huangqian@hhu.edu.cn

Chaozheng Zhu, Sisi Chen
Department of Multimedia
Nanjing Huiying Electronics Technology Corporation
Nanjing, China
E-mail: 370045744@qq.com

***Abstract*—This paper proposes the concept of the Internet of dog, and uses its perceptual tracking to track the behavioral trajectory of various dogs around the world, constructs a framework for analyzing the spatial and temporal trajectory of dogs, and answers our more unsolved mysteries. For noise data, this paper adopts sliding. The mean filter algorithm makes the behavior data significantly enhance the smoothness, and constructs a new police dog motion attitude fusion method. Compared with the Kalman filter method, it has higher real-time performance under the premise of ensuring accuracy. A new multi-sensor police dog data vest is designed and implemented according to the biological movement characteristics of the police dog. Based on multiple small and low power consumption sensors, a new police dog motion attitude fusion method is constructed, which can capture different posture data of the police dog, including standing posture. Sitting, lying, etc.**

Keywords-component; the internet of dog; police dog; pose fusion

I. INTRODUCTION

The Animal Network was proposed by the German Berlin researcher Andrew Curry in Nature in October 2018 to study the trajectory of tracking wildlife and answer questions unknown to biologists. However, since most of the animals being tracked belong to wild animals, especially some migratory birds, there are great difficulties in the maintenance and management of the sensing equipment (such as insufficient power and the need to replace the power supply). At present, dogs are the best animals of our human domestication. They are not only used as pets, but also in police duty or military border defense. At the same time, dogs are the animals that interact with us most. Further understanding helps us to better understand, domesticate, and manage them, making them play a bigger role in various fields. Therefore, we propose the concept of dog networking, and use it to track the behavioral trajectory information of various dogs around the world, construct a framework for analyzing the spatial and temporal trajectory of dogs, and answer more unsolved mysteries.

A. Related Work

Regarding the proposed various pose capture recognition technologies, according to their motion capture mechanisms, they can be divided into two categories: visual-based [1-6] or sensor-based [7, 8]. On the one hand, vision-based technology relies on information such as image feature points to solve motion trajectories and attitude information. On the other hand, with the advancement and maturity of microelectronics technology, electronic devices continue to develop toward miniaturization, making wearable human body recognition research possible. Based on the image motion capture method, although the user generally does not need to wear the device, the recognition accuracy is easily affected by illumination, occlusion, camera position and other environmental factors [6]. In contrast, sensor-based sensing technology is easy to implement, low-cost, and stable, and generally provides more reliable motion data [9].

On the one hand, thanks to the development of Micro-Electro-Mechanical Systems (MEMS), MEMS gyroscopes and accelerometer sensors are smaller, lighter in weight, lower in energy consumption, excellent in performance, and almost all kinds of needs. They are available in applications for motion pose reconstruction [10,11]. In 2017, Boston Dynamics shocked the world with its perfect backflip robot Atlas. A backflip action can be broken down into four stages, including take-off, flip, landing, and stabilization. Each stage needs to accurately estimate its posture in space and make correct feedback action control. At the same time, the magnetic sensor is combined with the inertial sensor [12], and the precise motion gesture recognition scheme has also been greatly developed. Attitude reconstruction based on sensor networks is a more accurate measurement method that can estimate the motion information of an object in real time without an external driver or camera. This method has the advantages of high accuracy, high efficiency, and ease of integration. Compared with the visual motion estimation system, it can show higher adaptability and lower error rate under the same motion information. However, due to its particularity, this paper proposes a new multi-sensor dog data vest, which can capture the static and dynamic movement information of the police dog standing, lying, biting and so on.

On the other hand, various motion estimation and recognition technologies such as k-Nearest (k-NN), CNN (convolution neural network) and SVM (Support Vector Machine) have been applied to fields such as 3D pose reconstruction[13, 14]. Although the current research on the estimation of the pose of the character is rich, the police dog belongs to an animal and often has frequent jitter in behavioral habits. This behavioral characteristic will generate a large amount of redundant jitter data, which greatly affects the estimation of the motion posture. accuracy. The traditional neural network classification model has limited ability to represent complex functions in the case of a small number of samples and computational units. The generalization ability is limited for the classification problem with many noise data. At present, there are relatively few motion pose estimations for police dogs. After comparison and analysis of multiple existing classification algorithms, the SVM algorithm is finally obtained, which is more accurate in classification accuracy and can better fit the real police dog posture[15, 16]. The redundant data generated by the shaking of the police dog has a strong generalization ability, which makes the classification and reconstruction of the police dog's movement posture more accurate.

B. Framework and contribution

The real-time reconstruction method of the police dog posture based on the multi-sensor data vest is to capture the sensor-percepted data through the data vest, and calculate the posture data, which is divided into training data and real data. The training data is used to update the deep neural network model, after which the real data is applied to the updated model.

In this section, a method for capturing the posture of police dogs based on ZigBee sensor network is proposed. Firstly, the inertial navigation unit, laser measuring sensor and barometer module are introduced, and a multi-sensor based police dog data vest is proposed. Then, the quaternion pose solution based on Mahony filter is derived.

The main contributions of this paper are as follows:

(1) Designed and implemented a new multi-sensor police dog data vest, providing intelligent motion sensing equipment for police dog battle scenes.

(2) For the noise data, the sliding mean filter algorithm is adopted, so that the behavior data significantly enhances the smoothness.

(3) A new police dog motion attitude fusion method is constructed. Compared with the Kalman filter method, it has higher real-time performance under the premise of ensuring accuracy.

The following part of the paper is as follows: the data preprocessing scheme of this study is introduced in Section 2; the feature extraction and classification are introduced in Section 3; the experimental results are explained in Section 4; the summary and outlook is given in Section 5

II. DATA PREPROCESSING

A. Police Dog Behavior Recognition based on Sensor Acceleration

In this study, two three-axis accelerometers were used, which were combined with a microcomputer to form a behavioral sampling node for police dogs to collect behavior data of police dogs. During the test, the posture detection sensor module (including the inertial navigation unit and the magnetometer) is installed on the joint connecting the shoulder skeleton with the skull and the pelvic bone. The height sensor module is attached to the abdomen of the police dog, and the main control module is attached to the pelvic bone. The sensor acceleration and angular velocity generated by the corresponding joint points during the movement of the police dog are collected. The collected data includes three postures of five police dogs, namely, sitting, standing, and squatting. As shown in Figure 1, each behavior of each police dog was collected twice, for a total of 60 samples.

Sitting standing squatting

Figure 1 Three postures of the police dog

B. Filter Out Noise Data

The sliding mean filtering here is mainly for the noise effect generated when the dog data is measured. Noise data here means that there is an error or an abnormality in the data (deviation Expected value) that interfere with the analysis of the data, which may be caused by hardware failures, programming errors, speech or optical character recognition programs (OCR) Identify errors, etc. The behavior data collected in this study inevitably contains noise data, which affects the accuracy of behavior recognition. The acceleration frequency generated by the noise data is about 10 Hz. The acceleration frequency generated by the target behavior of this study is below 4 Hz. According to the sampling frequency of 1000/6 Hz, the sliding average filter with window length of 30 is selected to filter the sensor acceleration data. It can not only filter out the useless information brought by the noise data of the police dog, but also retain the target behavior information as much as possible. Here, taking the sitting motion as an example, Figures 2 and 3 respectively compare the effects of the three-axis acceleration filtering noise data acquired by the sensor, and the gray box is the acceleration that is more affected by the shaking motion. As seen in Figures 2 and 3, the sliding mean filtering process can better remove the noise data in the behavior data.

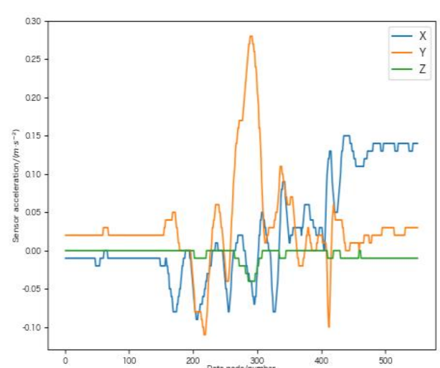

Figure 2 Before Filtering

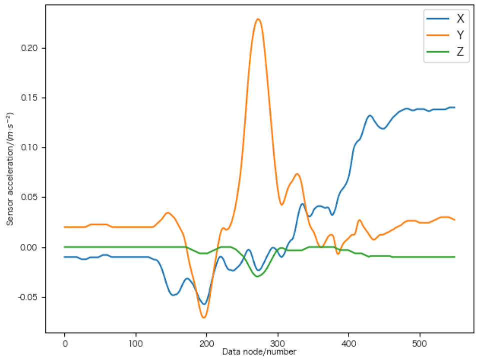

Figure 3 After Filtering

m Represents the strength of the magnetic field in the global coordinate system, m_b Represents a static interference source of a magnetometer, which is produced by a substance having a magnetic substance or that can affect the strength of a local magnetic field, and is calibrated by a plane calibration method; β_m Indicates measurement noise with less impact.

C. Attitude estimation based on Mahony filter

Attitude estimation is mainly to solve the orientation of the inertial navigation module, generally we used R to represent and its rotation equation is:

$$\mathbf{R}=\begin{bmatrix} \cos\gamma\cos\psi & -\cos\gamma\sin\psi & -\sin\gamma \\ \sin\theta\sin\gamma\cos\psi+\cos\theta\sin\psi & -\sin\theta\sin\gamma\sin\psi+\cos\theta\cos\psi & \sin\theta\cos\gamma \\ \cos\theta\sin\gamma\cos\psi-\sin\theta\sin\psi & -\cos\theta\sin\gamma\sin\psi-\sin\theta\cos\psi & \cos\theta\cos\gamma \end{bmatrix} \quad (1)$$

Three Euler angles θ, Y, Ψ among them representing the rotation of the inertial navigation module, the word R represents the rotation matrix of the body in three-dimensional space. Corresponding to any vector in 3D space V, coordinates in the global coordinate system V_n And coordinates in the body coordinate system V_b Satisfy:

$$V_b = R^T V_n \quad (2)$$

The above equation describes the nature of rotation (attitude) is the process of transforming the same vector in different coordinate systems.

D. Sensor measurement analysis

The inertial navigation unit consists of a gyroscope, an accelerometer, and a magnetometer. The gyroscope measures the rotational speed of the body coordinate system relative to the global coordinate system in the body coordinate system.

$$\omega_{xyz} = \omega + b_\omega + \beta_\omega \in \{B\} \quad (3)$$

b_ω Indicates the zero offset, which will produce zero drift overtime, and is calibrated using the single temperature calibration method[18]; β_ω Indicates measurement noise.

The accelerometer measures the external force of the body, and also uses the body coordinate system as the reference coordinate.

$$g_{xyz} = R^T(v - g_z) + b_g + \beta_g \in \{B\} \quad (4)$$

b_g Represents a zero offset that hardly changes with time; β_g Indicates measurement noise. v Indicates the acceleration of the body in the global coordinate system.

The magnetometer measures the magnetic field strength of the surrounding environment, and the reference coordinate system is the body coordinate system.

$$m_{xyz} = R^T(m + m_b) + \beta_m \in \{B\} \quad (5)$$

m Represents the strength of the magnetic field in the global coordinate system, m_b Represents a static interference source of a magnetometer, which is produced by a substance having a magnetic substance or that can affect the strength of a local magnetic field, and is calibrated by a plane calibration method; β_m Indicates measurement noise with less impact.

$$R_p = \hat{R}_p(g_{xyz}, m_{xyz}) \quad (6)$$

Also according to ω_{xyz} Construct another pose estimate R_t

$$R_t = \hat{R}_t(\omega_{xyz}) \quad (7)$$

By comparing the deviation of the attitude estimation value, the appropriate fusion algorithm is selected to obtain an accurate and reliable body rotation attitude.

E. Quaternion attitude solution based on Mahony filter

This paper proposes a Mahony filter based on[7]The algorithm for data fusion has higher real-time performance than the classical Kalman filter. The framework is shown in Figure 4.

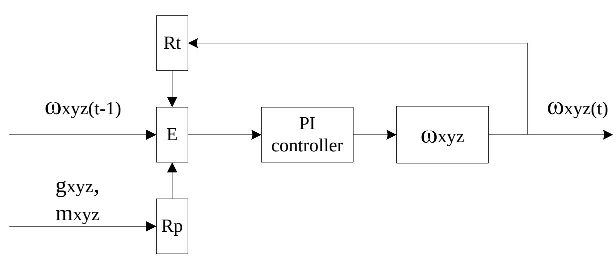

Figure 4 Mahony filter algorithm principle

First, an attitude estimate can be constructed based on the accelerometer and magnetometer R_p And then use the information of the gyroscope angular velocity to obtain another attitude estimate R_t , Mahony filter by comparison R_p versus R_t The deviation between them is used as a correction amount E as an input to the PI controller.The output of the PI controller measures the angular velocity as a gyroscope ω_{xyz} .The correction value is error compensated so that the final output is stable, true and reliable.The Mahony filtering algorithm is represented by the following steps:

1) Attitude estimate R_p , R_t to Update the equation:

$$R_p = \hat{R}_p(g_{xyz}, m_{xyz}), R_t = \hat{R}_t(\omega_{xyz}) \tag{8}$$

2) Calculate the offset correction amount E:

$$E = \hat{E}(R_p, R_t) \tag{9}$$

3) Use pi controller to compensate for errors:

$$E = \hat{E}(R_p, R_t) \tag{10}$$

Solve quaternions using the Runge-Kutta method:

$$\begin{pmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{pmatrix}_{t+\Delta t} = \begin{pmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{pmatrix}_t + \frac{\Delta t}{2} \begin{pmatrix} -\omega_x \cdot q_1 - \omega_y \cdot q_2 - \omega_z \cdot q_3 \\ \omega_x \cdot q_0 - \omega_y \cdot q_3 + \omega_z \cdot q_2 \\ \omega_x \cdot q_3 + \omega_y \cdot q_0 - \omega_z \cdot q_1 \\ -\omega_x \cdot q_2 + \omega_y \cdot q_1 + \omega_z \cdot q_0 \end{pmatrix} \tag{11}$$

Finally, the calculation formula of Euler angle is obtained:

$$\mathrm{Roll(Roll)} = \sin^{-1}(-2(q_1 q_3 - q_0 q_2)) \tag{12}$$

$$\mathrm{Pitch} = \tan^{-1}\left(\frac{2(q_2 q_3 + q_0 q_1)}{q_0^2 - q_1^2 - q_2^2 + q_3^2}\right) \tag{13}$$

$$\mathrm{Yaw\ angle} = \tan^{-1}\left(-\frac{2(q_1 q_2 + q_0 q_3)}{q_0^2 + q_1^2 - q_2^2 - q_3^2}\right) \tag{14}$$

According to the above algorithm, the Euler angle of the inertial navigation module can be solved, thereby providing data support for the subsequent police dog motion estimatio n.

III. FEATURE EXTRACTION

A. Introduction and research methods of feature extraction

Feature extraction and selection are connected to the two processes of data acquisition and motion classification, which is a fundamental problem of pattern recognition. Its quality will directly affect the classification performance of the recognition system. Feature extraction and selection are usually not general. Different systems have different effects on the classification recognition effect because the recognition object and the classifier used are different. Although there is no unified theoretical analysis method for feature extraction and selection, through the statistical analysis of the signal characteristics used in the police dog motion pattern recognition system in recent years, the feature extraction methods of acceleration signals can be summarized into three categories: time domain analysis , frequency domain analysis and time-frequency analysis.

In order to eliminate the influence of the binding mode of the sensor on the behavior recognition research, the geometric mean acceleration of the three axes of the sensor acceleration is obtained, and the feature extraction is performed on this basis. The formula is as follows:

The seven conventional acceleration time domain features include maximum, median, interquartile range, mean, standard deviation, skewness, and kurtosis. The maximum, median, interquartile range, mean, and standard deviation are all descriptions of the acceleration distribution. Skewness is a statistic used to measure the direction and extent of the distribution of acceleration.The kurtosis reflects the steepness of the acceleration at the peak of the data curve.

Skewness is a measure of the asymmetry of the distribution of random variables, expressed in β, which is calculated as:

$$\beta = \frac{\mathrm{E}(X-\mu)^3}{\sigma^3} \tag{15}$$

Where μ is the mean and δ is the standard deviation

Its meaning is: when the distribution is completely symmetrical, $\beta = 0$, the normal distribution is symmetrical, $\beta > 0$ When the distribution is positively biased, also known as right deviation, the tail of the distribution above the mean has a serious extension to the right; $\beta < 0$ When the distribution is negative, it is also called left-biased. The tail of the distribution below the mean extends to the left.

Kurtosis measures the steepness of the non-middle part of the random variable and the thickness of the tail at both ends. It can also be simply used as a measure of the flatness of the distribution. The formula is:

$$\beta_4 = \frac{\mathrm{E}(X-\mu)^4}{\sigma^4} - 3 \tag{16}$$

Where μ is the mean and δ is the standard deviation. Wh en comparing the kurtosis of the two distributions, they must have the same mean and variance.

When the data is normally distributed, its kurtosis is 0, the positive kurtosis indicates that the data distribution is more slanting than the middle peak of the normal distribution, and the two tails are heavier; the negative kurtosis indicates that the data distribution is flatter than the normal distribution peak. The two tails are lighter.

B. Feature processing

First, the study normalized and windowed features before using features for classification. Normalization uses the normalization method, and the normalized features will obey the standard normal distribution. The calculation formula is:

$$z_i = \frac{x_i - u}{\sigma} \tag{17}$$

In the formula: x_i Characteristic vector x_i Component, Is the result of its normalization; u with σ Feature vector x The mean and standard deviation of all components. The normalized features are distributed in the [-1,1] interval, and the processed samples are shown in Figure 5.

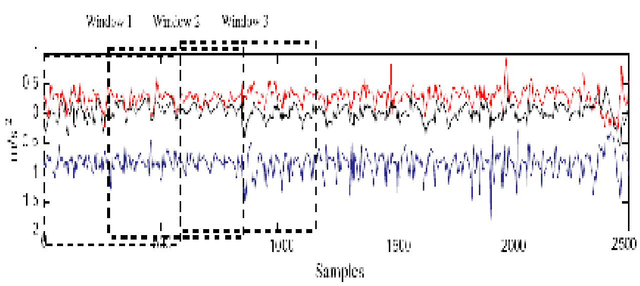

Figure 5 window processing

Then, the initial feature set composed of the normalized features is used to perform feature optimization using the ant colony algorithm to reduce feature redundancy. The ant colony algorithm is a preferred method to simulate the foraging behavior of real ant colonies [14-15].A single ant in nature chooses to feed the road based on the concentration of pheromone. Roads with shorter distances will have more round trips, so there is a higher concentration of pheromone levels, which induces more ants to choose shorter roads, thus making ant colonies more and more concentrated on the shortest foraging roads. .

The core of the ant colony algorithm is the ant selection feature point transfer rule and pheromone update rule. The calculation formula for the feature-preferred ant colony algorithm transfer rule is:

$$p_\iota(\mathrm{j}) = \frac{\tau_{\iota-1}(\mathrm{j})^k \eta(\mathrm{j})^\beta}{\sum_{\iota \in k} \tau_{\iota-1}(\mathrm{j})^k \eta(\mathrm{j})^\beta} (\mathrm{j} \in \mathrm{K}) \tag{15}$$

In the formula: $p_\iota(\mathrm{j})$ For the first i Ant selection feature point in the second iteration j Probability value; $\tau_{\iota-1}(\mathrm{j})$, Feature point after iteration j Pheromone level value, when initializing $\tau_0(j)$ Take 1; $\eta(j)$ To use a single feature point j Classification recognition rate; α Take 1 for the pheromone heuristic factor, β Take 2 for the feature recognition rate heuristic factor; K It is an optional feature point set, that is, a feature set that has not been used yet.

When the ant colony completes a search, the pheromone of each feature point needs to be updated. The calculation formula for the pheromone update rule is:

$$\tau_\iota(\mathrm{j}) = (1 - \rho) \times \tau_{\iota-1}(\mathrm{j}) + \Delta\tau_\iota(\mathrm{j})$$
$$\Delta\tau_\iota(\mathrm{j}) = \varepsilon \sum_{\alpha-1}^{m} \mu(\alpha), (\mathrm{j} \in Z_\iota(\alpha)) \tag{18}$$

In the formula: $\tau_i(j)$ For the first i Feature point after iteration j Pheromone level value; ρ Take 0.5 for the pheromone volatilization coefficient; $\Delta\tau_i(j)$ For the first i The pheromone increment after the iteration; ε Take 0.5 for the increment coefficient; $\mu_i(a)$ For the first i Iteration after ant a The recognition rate of the obtained feature subset; $Z_i(a)$ For the first i After iteration, ants a Search for a subset of features generated; m For the number of ants.

When performing feature selection, first determine the number of features of the target feature set. In this study, 28 is taken, that is, the algorithm needs to perform 28 iterations. The ant is selected with the number of features in the initial feature set to perform feature selection. After the iteration, each ant selects a subset of the feature set and selects the subset of the feature set with the highest recognition rate as the target feature subset.

Ⅳ . TEST RESULTS AND ANALYSIS

A. Experimental results and analysis

In order to verify the feasibility of the research method, before the experiment begins, the labeled data samples are divided into static data and dynamic data. We first classify all the group data measured by the multi-sensors with different classifiers, then A set of data in a data set is classified through a series of processes to simulate the zgesture recognition of a single sensor. This experiment mainly uses dynamic data to judge the static attitude of the police dog. For example, if the data is sitting on the cymbal, the machine learning algorithm can judge its posture as lie , we extract 70% of the data as the training set, and the remaining 30% as the test. data.

The test data is respectively brought into the svm classifier, and the decision tree classifier and the artificial neural network classifier are added to record the time and classification accuracy of each classifier to complete the training.

After obtaining the trained classifier, the test is performed with the remaining 30% of the data. The accuracy and training time of different method classifications are shown in Table 1:

TABLE 1 ACCURACY AND TRAINING TIME FOR DIFFERENT METHOD CLASSIFICATIONS

	SVM	Decision tree	Artificial neural networks
Static accuracy (based on single sensor) (%)	79.41	70.23	75.96
Static accuracy (based on multi-sensor) (%)	85.33	80.12	84.56
Dynamic accuracy (based on single sensor) (%)	70.41	64.37	69.21
Dynamic accuracy (based on multi-sensor) (%)	64.66	56.73	70.34
Based on multi-sensor dynamic training time (%)	139.7	140.1	14.4
Based on single sensor dynamic training time (%)	63.7	65.1	37.6
Based on multi-sensor static training time (%)	186.5	167.3	10.7
Based on single sensor static training time (%)	64.1	34.2	9.6

After comparison, for all experiments, based on the single sensor classification, only the data of the three-axis acceleration, that is, the data of an acceleration sensor, is difficult to classify for the lie and the station. It can be clearly seen from the above figure. Whether it is based on multi-sensor or single sensor, svm algorithm is the preferred algorithm. The classification accuracy based on multi-sensor is significantly higher than that of single sensor. We have not found a better algorithm to optimize. After the database matures, we will Improvements will be made on this basis. Of course, single sensors are superior to multi-sensors in terms of time and cost. Our next step is to strive to achieve a single sensor-based attitude classification that is more accurate than the accuracy of multiple sensors.

Ⅴ.CONCLUSION

This paper proposes a single sensor-based police dog state estimation method, and builds a real-time police dog attitude reconstruction system, which provides an intelligent, convenient and over-the-horizon interaction mode for police dogs. Aiming at the biological movement characteristics of police dogs, a new method of blending postures of police dogs is constructed, which can capture different posture data of police dogs, including standing posture, sitting posture, and lying posture. On this basis, a complete set of police dog over-the-horizon is also developed. Combat equipment, there are now a number of sets of equipment directly used in the Nanjing City Police Dog Institute to undertake the actual work, has formed the prototype of the dog network. In the future, we are ready to expand the scope of our dog network application, starting with police dogs, gradually spreading to military dogs, pet dogs, and even some special dogs (for example, guide dogs, sheepdogs, etc.), and strive to study a dog that can be applied to all dogs. Wearable equipment, perceptually track their behavioral trajectory data, construct a framework for canine space-time trajectory analysis mining, and explore more unknown secrets.

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